A Review of Algorithms for Credit Risk Analysis

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Abstract

The interest collected by the main borrowers is collected to pay back the principal borrowed from the depositary bank. In financial risk management, credit risk assessment is becoming a significant sector. For the credit risk assessment of client data sets, many credit risk analysis methods are used. The assessment of the credit risk datasets leads to the choice to cancel the customer's loan or to dismiss the customer's request is a challenging task involving a profound assessment of the information set or client information. In this paper, we survey diverse automatic credit risk analysis methods used for credit risk assessment. Data mining approach, as the most often used approach for credit risk analysis was described with the focus to various algorithms, such as neural networks.

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Introduction

One of the banks' most critical and key procedures is the loan allocation process for assessing loan requests. This crucial process involves the collection, analysis and final credit decision of the various factors that are used for the evaluation of credit applications, from sources like credit application forms, inter-bank data sharing, credit office data and the key internal bank data.

In a traditional evaluation approach, banks approve or reject applications from commercial and/or retail customers, by the usually subjective views of the credit allocation specialist. The "credit scoring technique" or more frequently known as "Scorecard" is also an approach for assessing loan requests. The scorecards will predict the likelihood of an applicant repaying the credit he/she requested and address the issue of whether or not the loan defaults at any moment. An application scorecard is created in terms of credit risk based on previous statistics, by classifying it as good or bad. Past loan applications are evaluated to identify features which have an important impact on the discrimination of good and bad credit risk applications (Anderson, 2007). The benefits of using loan allocation scorecards can be summarized as better choices, faster and cheaper, more coherent loan choices, measurable risk management and reduced transaction expenses.

Data mining is a significant field of studies, aimed at acquiring large amounts of data and analyse it with machine learning. Currently, data mining is common in the banking industry, as there are effective analytical techniques to identify information relevant for credit scoring. The primary focus is to leverage an enormous amount of information available in databases to make key decisions.

The borrower/client/customer is obliged to reimburse the main and future interest if a loan from a bank or financial institution has been granted. The most important thing is the amount borrowed, and the bank's interest rates. Credits are generally secured or unsecured. A loan secured includes a commitment for a loan to an asset, such as a vehicle, house etc. If the borrower makes an error or fails to pay back the loan, the lender is entitled to the asset. An unsecured credit option is not preferred, and not usual. If the borrower fails to repay the insecure debt, the lender has no right to withdraw anything.

The bank first checks the client's profile and documentation when approving a customer loan. Every bank has a credit score for each client, which is expressed as numbers based on a credit file of the borrower (Chopde et al., 2012). This process is referred to as a loan assessment that requires time, but is usually a binary decision, resulting with an approval or a rejection. Credit activity blows under marking circumstances is at the core of the bank. The two main reasons for the need for an expert support system are the absence of accurate methods of measuring the lack of public credit risk system and credit risk in many banks (Sudhakar & Reddy, 2014).

Many risks associated with bank loans, for bank and for those who get the loans. The risk assessment in bank loans should be understood as the significance of the risk. Credit risk is the risk that the loan won't be returned back on time or at all; liquidity risk is the risk that too many deposits will be withdrawn too quickly, leaving the bank short on immediate cash; and interest rate risk, the risk that the interest rates priced on bank loans will be too low to earn the bank adequate money (Hamid & Ahmed, 2016).

In order to rank the candidates in good and bad classes, the banking system measures the accuracy of the data sets. The candidates in the good classes are very likely to return the cashback to the bank. The candidates in the bad class are not likely to return the cash to the bank and are thus defaulting on the loans. Different kinds of credit risk assessment methods are used to minimize the loan data defaulter rate (Bask et al., 2011). Even with a tiny increase in the precision of loan assessment, sometimes enormous losses can be decreased. The advantages of a reliable credit risk dataset are that credit scoring costs are reduced, excellent decision-making takes less time, and loan collection risks are avoided. Because the credit risk assessment plays a key role in the banking sector and is very critical and a major challenge facing banks, accurate classification of loan information in order to prevent economic loss plays a significant role. The decrease in defaulter's rate in the credit risk data set which is not reliable gives motivation towards this field (Pandey et al., 2013).

Literature review

Close to the competitiveness and profitability of the Bank is the quality of the credit portfolio of the bank. As the amount of highly creditworthy clients rises, the quality of the bank loan increases. Credit scoring is the main decision support system used to assess the applicant's creditworthiness. The credit scoring can, therefore, be defined as the method of modelling an applicant's creditworthiness (Crook et al., 2007).

There are various definitions in the literature for credit scoring. It is described by using statistical methods as a guide to making a loan choice that converts the appropriate loan variables into numerical action (Anderson, 2007). The Malhotra and Malhotra (2003) described as an analysis model that has empirically constructed data from past applications, using the default probability, to predict the creditworthiness of applicants.

The origins of scoring systems can be traced in the 1930s when certain mail-order businesses began using a scoring system to decrease discrepancies between loan analysts. The management of credit risk has been a problem for companies working in the financial industry because of the compelling duty for credit analysts to perform military services during World War II, resulting in an absence of credit risk specialists. Companies, therefore, wanted analysts to write down the laws they used to grant credit. Non-experts used these guidelines to assist businesses with their loan decision systems, which then led specialist systems (Thomas et al., 2002).

The scholarly literature on credit scoring dates back to the 1940s when Durand published his work outcomes in order to detect credit factors which significantly affected a good and bad classification of loan applications based on the concept of loan scoring "…same characteristics could be used in separation of the groups within the same group…" (Durand, 1941).

By using information from businesses working in the manufacturing sector in the USA, Altman (1968) has used a discriminatory technique of assessment. In his research, he created a general accuracy model to predict failure of the company. Because banks provide a broad variety of products, the number of applications for credit has increased significantly. This enormous rise in demand in the banking industry led to increased requests for credit scoring applications. Banks have started assessing almost any application of credit for consumer credit, credit cards, small business loans, and home loans (Emel et al., 2003).

Beaver (1966) submitted a survey analysing the possible predictors used to predict bankruptcy. He statistically demonstrated that several loan variables were used mainly to assess the likelihood that a company would become bankrupt.

Because only historical data were taken into account in early loan scoring models for the accepted applications, they could not learn the qualities of the applications rejected. Feelders (2000) has used accepted and rejected applications to create a mixture model and demonstrated that the model's efficiency improves significantly when rejected applications are included.

A good assessment of the credit card applications through credit rating methods resulted in banks to use credit ratings for home loans and small business loans in the 1980s (Thomas et al., 2002). The amount of applications has so much increased that it has become economically difficult to apply the traditional strategy in which a loan expert has assessed requests one by one. The willingness of both applicants for the credit and banks to assess requests in a fair moment motivated banks to use the credit scoring in the assessment of the applications for credit (Lewis, 1992).

Banks are becoming more focused on carrying out several empirical research to benefit from the classification methods, which are already effectively introduced and implemented. This allows them to differentiate between good and bad credit applications and create policies that maximize profit from both new and existing clients (Finlay, 2010).

In order to assess loan applications for separation of acceptance or rejection, the credit score method utilizes the previous credit record to obtain a quantitative model. Credit assessment criteria are applied constantly to all loan applications in the credit scoring system. Credit decisions can be made promptly with the credit scoring system. Furthermore, because of the short time needed to complete loan request, credit scoring retains increasing customer satisfaction. It can also offer a holistic performance measurement strategy (Nisha, 2017). Credit scoring models are considered one of the most effective business statistical applications (Bailey, 2004).

A lot of quantitative methods were used for credit scoring purposes in the literature. There are several statistical methods for evaluating credit risk, although these approaches have trouble modelling complicated economic systems, as they are based on fixed features and statistical assumptions. Studies comparing statistical methods and machine learning methods to evaluate credit risk shows that machine learning techniques are more efficient than statistical techniques (Saberi et al., 2013).

Credit risk evaluation by nature is a classification problem. A binary classification technique using Support Vector Machines (SVM) for the issue of a quantitative credit risk assessment is presented by Harris (2013). In the study, the SVM technique was applied by using both broad and narrow data where broad means less than 90 days past due and narrow means more than 90 days past due. The performance comparison of the models showed that using broad data outperform the models developed using narrow data. Another research using SVM to evaluate credit risk using SVM in conjunction with the choice of developmental parameters was presented by Danenas and Garsva (2012).

Useful research, which showed superior efficiency compared to statistic loan assessment models conducted by Sousa et al. (2016) suggested a fresh dynamic structure for credit risk assessment. The technique comprises of sequential knowledge through the implementation of new information that enables the projections to be adjusted with changing information volumes.

For Jordanian business banks' lending decisions, Bekhet and Eletter (2014) implemented artificial neural network models. In the neural network model instead of logistic regression, the radial function model was used. Though the neural network model is less accurate overall, the writers have found that it is more potent to identify clients with the default option.

Kao et al. (2012) created a template which includes two techniques: the Bayesian method and the two-stage regression tree process. The first step is to develop a hierarchical Bayes model for clients that represent reimbursement choices and credit-use behaviours to predict quality ratings. In the second stage, these anticipated client performance results are used as an input into the Classification and Regression Trees (CART) algorithm, as are client credit reports and demographic information. CART results are used to develop decision-making guidelines to determine whether the applicant is to grant credit, to establish loan boundaries, annual percentage rate, and other bank products levels. Based on these outcomes, the authors conclude that the credit report of a cardholder is the most explanatory of credit scoring and demographic factors are of less significance because they have less credit scoring effectiveness.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed as a credit scoring model in the work of Akkoc (2012) which uses statistical techniques and Neuro-Fuzzy. The efficiency of this suggested model was evaluated against the use of credit card information from an international bank operating in Turkey, Linear Discriminant Analysis, Logistic Regression Analysis and Artificial Neural Network. The ANFIS technique resulted in a high average correct classification rate and lower estimated error cost.

Logistic regression is among the well-known and robust credit scoring and evaluation methods that have been widely used in the literature. By evaluating the features of candidates and the features of loans and of the branches and credit officers, Van-Gool et al. (2012) implemented logistical regression. In another logistic regression research by Kinda and Achonu (2012), the applicant has evaluated the socio-economic features, the loan characteristics and the experience of credit officers. By evaluating credit characteristics, the applicant characteristics and the connection between the applicants and the bank, Dinh and Kleimeier (2007) used logistic regression.

Recent studies have shown that traditional techniques of statistical analysis and artificial intelligence (AI) typically apply to the choice of features that can enhance credit risk identification accuracy.

Regarding traditional statistical techniques, existing research examines factors that affected customers' credit risk, mainly by statistical methods like Multiple Discriminant Analysis, Multiple Logic Regression, and Markov Chain. Pinches and Mingo (1973) and also McAdams (1980) in his research proposed Multiple Discriminant Analysis to study the influencing factors of the credit rating. By using the Nested Logit Model (NLM) Pishbahar et al. (2015) analysed 779 farmers' information and found the main impacts for repayment. By creating a logical regression model, Karan et al. (2013) examined loan assessment indicators. With a technique of quantitative assessment, Afolabi (2010) evaluated some socioeconomic features of 286 small farmers in Nigeria). The Ordering Probit Regression, ANOVA and Survival Duration Models were used by Karminsky and Khromova (2016) to investigate factors influencing credit risk. With the Fuzzy rough definition technique and the F test method, Bai et al. (2019) evaluated their credit qualifications). Zhang and Chi (2018) applied a genetic algorithm to analyse the credit rating of customers. Petropoulos et al. (2016) proposed a hidden Markov model for credit rating predictions and yield significantly more reliable prediction. Hwang (2013) made comparisons with traditional statistical techniques and the results show that ordered logit regression and ordered probit model are the most successful models. Shi et al. (2016a) suggested a new method to differentiate the level of the customer through fuzzy cluster analysis. Shi et al. (2015) combined logistic regression and correlation analysis to extract features. R cluster analysis and coefficient of variation were also applied to selection features (Shi et al., 2016b).

Researchers lately suggested an approach to hybrid information mining in the design of an efficient credit-scoring model concerning Artificial Intelligence (AI) technologies. The selection mechanism for credit scoring is examined by the neural network, support vector machine (SVM), genetic algorithm and other techniques. Akkoc (2012) proposed a three-stage hybrid Adaptive Neuro-Fuzzy Inference System credit-scoring model. The findings showed that total assets, total liabilities and operating profit margin are essential to the credit risk of the American examples, Huang, Chen and Hsu implemented the neural network technique in their research (Huang et al., 2004). In the evaluation of the credit-risk, Kim and Ahn (2012) investigated SVM and showed that SVM's generalizing performance can be further improved through the selection of functionality. Hájek (2011) used genetic algorithms to select input variables. Hájek and Michalak (2013) have demonstrated that wrappers have improved the accuracy of US and European datasets better than filters.

Most of the risk characteristics concentrate on financial indexes or customers' private data, which disregards the macroeconomic variables. Second, most of the rating systems concentrate only on classification accuracy but are not able to pick the main variables that affect the willingness of the customers to make repayments.

Types of classifiers for credit risk analysis

For the better and more reliably analysed credit risk, different kinds of methods are used for the evaluation of credit datasets.

Bayesian Classifier

The Bayesian network is known as the belief network. Bayesian is an acyclic direct graphic or Directed Acyclic Graph statistical model (Pandey et al., 2013). Every node in the graph shows a random variable in which the edges represent the functions of the respective variable. The Bayesian network is an acyclic chart which represents a distribution of joint likelihood across a random variable.

One of the most popular probabilistic methods applied in data mining is the Bayesian model. Coined by Thomas Bayes in a paper published two years after his death (Bayes, 1763) and later independently complemented by Pierre-Simon Laplace in (Laplace, 1812) states that the following:

$$P(h|d) = \frac{p(D|h)P(h)}{P(D)}$$

Where,

- P(h): the prior probability of hypothesis h-prior
- P(D): the prior probability of training data D-Evidence
- P(D|h): the probability of D given h-likelihood
- P(h|D): the probability of h given D-posterior probability

Naïve-Bayes Classifier

It is a straightforward probabilistic classification based on the rule of Bayes. This classification is called naive as it assumes that the characteristics of a class are each other autonomous (Pandey et al., 2013), (Huang et al., 2004). In order to compute parameters like mean and variance, another important classification variable is necessary for the Naïve Bayes classifier, a small amount of data.

Bayesian Belief Network

A Bayesian Belief Network is a Directed Acyclic Graph which contains several nodes that represent variables with a finite group of states and edges that are the probabilistic causal dependence on the variables. Nodes with edges are known as

"child" nodes and the nodes from which the edges get underway are known as "parent" nodes, and nodes without arches directed to them are known as "root" nodes. The Directed Acyclic Graph represents the causal dependence structure between nodes and provides the equitable part of causal reasoning in the Bayesian Belief Network and therefore the relationship between the variables and the respective states gives a quantitative portion consisting of a Conditional Probabilistic Table.
The chain rule states that a Bayesian Network represents the general distribution of all variables represented by the Directed Acyclic Graph. For each node of the network, it is possible to measure the margins and conditions of probabilities.

Decision Tree

The Decision Tree is a model that maps the comment on a branch element in order to conclude a target value in leaves. This is one of the best monitored supervised techniques. Each inner node or non-leaf node with an input function is marked in this learning method. Each leaf node in the tree has a class or probabilistic class distribution (Bask et al., 2011) (Curran & Orr, 2011). The branches between the Nodes indicate potential values that can be found in those characteristics, while the terminal nodes show the final value of the factors to be observed (Wang et al., 2005).

K-Nearest Neighbour

KNN is the technique of classification and regression that is nonparametric. This includes both a favourable and adverse training package. It is also called the lazy algorithm. It uses no data point for practice to generalize (Islam et al., 2007). This implies that the training stage is very quick, that all training information is maintained. During the test stage, all training data are necessary. A distance measured is used to determine the k-instances of a training dataset (Huang et al., 2006b). The most common Euclidian distance is used for the truly valued input variable.
Euclidean distance is calculated as:

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

However, depending on the dataset, other distance or similarity metrics can be used, such as Minkowski Distance, Jaccard, Simple Matching Coefficient, Cosine Similarity etc.

In KNN regression, the prediction is based on the average or median of most similar K cases. KNN can be calculated as a class with the largest frequency in most comparable cases when KNN is used for classification. Each case is taken as a forecast to vote for their group and the class that has the most votes.

K-Means

Represents an unsupervised learning technique that is used when unlabelled information is provided. The aim of this algorithm is to discover groups in the information with the number of groups of K. The algorithm operates to assign one K-group to each data-point according to the characteristics given (Curran & Orr, 2011). K-cluster centroids, which may be used for training information as low-marked new data and labels. A set of functional vectors is presented as a clustered dataset in this algorithm. Randomly selects the amount of seed by k to be the cluster centre. Assign the nearest data point to the cluster.

K-Means and its improved version K-Medoids are among the most common clustering algorithms. However, their disadvantages are that one needs to know the number of K clusters before running the algorithm, the algorithms are sensitive to outliers, noise and the initial position of the centroids greatly affects the result of the algorithm.

Other clustering techniques that are often used to alleviate the above problems are hierarchical clustering techniques (AGNES and DIANA), density-based clustering, grid-based clustering etc.

Important to mention is that clustering algorithms cannot be used to predict credit rating (or any other prediction). Instead, they are commonly used in combination with a supervised classification algorithm, often as a pre-processing step in data mining.

Artificial Neural Network

A group of neural networks connected to a weighted node is an artificial neural network (Dhaiya et al., 2016). Each node can reproduce a creature's neuron, and the synaptic connections between the neuron are the same as that between these nodes. The neural network comprises three layers, named multi-layer perceptron, which is the input, hidden layer and output layer (Olafsson et al., 2008). In the MLP the network of layers connected as a layer of input units connected to the layer of hidden units which are then connected to a layer of output unit.

Multilayer Perceptron

MLP was commonly used for credit risk in the economic sector. For supervised machine learning used back-propagation algorithm. It includes the input layer, output layer and one or more hidden layers between them (Chen and Huang, 2003). Every layer is fully interconnected. Except for the input layer, the processing component for each layer is called the nodes that act as a neuron. Each node in one layer is linked to another node in the next layer by weights. There are several neuron layers with non-linear activation. The network can learn the connection between input and output vectors from these layers.

Extreme Learning Machine

ELM is developed by Huang is developed for generalized single hidden layer feed-forward networks (Chen and Huang, 2003). ELM randomly selects the hidden node parameter that can represent the network as a linear system and analytically calculate output weights (Huang et al., 2006a). ELM tends to achieve a minimum training mistake and the minimum weight standard which results in successful wider use. ELM is very quick to learn and offers excellent efficiency in generalization in many artificial and true applications (Zhou et al., 2012). ELM is a novel training algorithm for single-layer feed-forward network and is very effective and efficient. Given N distinct training samples $(x_i, t_i) \epsilon R_n * R_m, (i = 1, 2, \dots, N)$, the output of an SLFN with N hidden nodes can be represented by:

$$O_j = \sum_{i=}^{N} \beta f_i(x_i) = \sum_{i=1}^{N} \beta f\left(x_j; a_i, b_i\right), j = 1, \dots, N$$

Where, O_j is the output vector of SLFN with respect to input sample $x_i.a_i = [a_{i1}, a_{i2}, \dots, a_{in}]T$ and b_i are the learning parameter generated randomly of the jth hidden node that is $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]T$ is the link connecting the jth hidden node and the output node. $f(x_j\,;\, a_i\,, b_i)$ is the activation function of the original ELM.

Support Vector Machine

Support vector machine is yet another supervised learning system, which examines data for classification and regression with a corresponding learning algorithm. SVM constructs a hyper-plane or set of hyper-planes in a high or infinite-dimensional space which can be used for classification, regression and other tasks (Chorowski et al., 2014). SVM was first suggested for machine learning by Vapnik in 1995 and demonstrated its efficiency in many areas. A good distance from the closest training information point (functional margin) accomplishes a good separation (Danenas & Grasva, 2015). The larger the margin is the lower the generalization error of the classifier (Huang et al., 2004b). SVM is helpful in text and hypertext because its application can reduce significantly the need for labelled training instances in the inductive and transductive standard (Hearst et al., 1998). The SVM also allows the classification of images. Many experimental findings have shown that SVM provides more precision than traditional query refinement (Hui & Gang, 2011). Handwritten characters can be recognized using SVM.

The decision function f(x) is given by:

$$f(x) = sgn(w, x + b)$$

To compute optimal hyper-plane the optimized problem is to be solved, Minimization: 1÷ 2$\|w^2\|$, Subject to:$y_i = ((w.x_i) + b - 1) \geq 0$.

The margin of hyper-plane = $2/||w||$ equivalent optimization is:

$$\sum_{i=1}^{l} y_i \alpha_i = 0$$

Ensemble the Classifier

An ensemble of classifiers includes a group of separately trained basic classifiers. The choice is made by the basic classifiers to set a classifier. By voting, the new and invisible cases shall be classified collectively. The vote may or may not be weighted. The basic classifiers are joined together to achieve greater efficiency in a mixed classification than the single classifier. Some researchers have shown that by using the aggregating approach the classifiers can easily achieve improved accuracies on the aggregation of the individual classifier in classification application as well as credit evaluation. Different approaches to aggregation used for enhancing the accuracies of the classifier. The most aggregation approaches are bagging and boosting (Pandey et al., 2013).

Bagging. The Bagging is afore standing ensemble strategy introduced by Breiman in 1996 (Hui & Gang, 2011). This is a Meta algorithm for machine learning, intended to enhance the stability and exactness of machine learning algorithms that are used in statistical classification and regression. It helps to reduce fitting. The bagging is an average approach to the model. The comparable classification is mainly selected as a basic classifier in the bagging. With bagging, distinct decision structures can be produced by separate training Jain and Kumar (2007) set of having the same size and that is done by sampling the training set "with replacement".

Boosting. Boosting is a sequential ensemble technique, attempt adding new models that are successful when earlier models are missing (Pandey et al., 2013). The aim of boosting is not to lower the variance. It is suitable for high bias designs with low variance. The majority of stimulating algorithms are a weak distribution classifier and they are added to a powerful rating (Huang et al., 2006b). The boosting generates a classification ensemble by again sampling the training data set coupled with the cost function or majority voting.

Conclusion

Risk is a component of the functions of the banking system that cannot be fully eliminated but decreased by the use of suitable methods. One of the primary aims in the banking system is to keep a sustainable and sound credit system, beginning with the credit application and ending with credit closure. Credit risk, which is the most essential risk form for banks, is strongly linked to measuring and managing the excellence of this procedure.

In the highly complex banking sector today, no payback or credibility measurement should be carried out carefully, quickly, accurately and in a realistic way. As a result, crediting effectiveness and customer response rates are increased and we can evaluate applications more quickly and for more applicants. The failure of the banks to judge credit requests leads to inefficient use of funds. If the bank credits an applicant with pretending that this loan is not risky, but the issue will be that there is no repayment, or bank does not grant the credit to an applicant who is not going to have the problem of no payback causes the bank to make severe losses.

The primary objective in the traditional technique of credit evaluation is to only grant credit to clients who are good at repaying the loan. Credit applications are evaluated by the credit underwriting specialists. If the request is accepted, the applicant's credit is opened. In this procedure, however, the customer's discontent is caused because of the inconsistencies in the credit decision system and the absence of assessment of each applicant with equal and objective variables as the subjective judgment of the loan underwriting professional is used.

Credit requests are assessed using a decision support system as a scorecard using distinct classifiers in the new strategy used by loan rating systems. Using this strategy, it aims to assess the credit applications that grow quickly, quicker, more efficiently and more accurately. The system's velocity is linked to the objective nature of the loan assessment and decision-making time. The efficacy and accuracy of the template used in the credit assessment method rely on the predictive strength and consistency.

In this paper, different types of classifiers are discussed and different types of ensemble classifiers are briefed.

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